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Passenger preferences for (emerging) public transport access/egress modes

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Summary

By combining the extended range, flexibility, environmental and health benefits of cycling with the space and energy efficient transport over longer distances by train, the bike-train combination can offer a true and attractive alternative to the private car. Yet despite the increase range offered by the bicycle, many destinations are still not accessible within a typical cycling distance (~5km). To further increase the access radius of train stations, emerging electric micromobility alternatives may provide an attractive and viable alternative.

To analyse this potential of micromobility, we carry out a stated preference survey among the Dutch population, testing the perception and preferences for a shared e-bike, e-step and e-moped and compare that with existing solutions that many are familiar with, namely the shared bicycle (OV fiets), local public transport (bus, tram, metro) or walking.

Our preliminary results show that to a large degree, respondent prefer to use existing modes of transport. Walking is most preferred for shorter distances (up to ~15min), after which cycling and public transport are equally likely to be selected. The choice for either comes down to respondent's existing travel behaviour: frequent cyclist would prefer using the bicycle and vice versa. Shared electric modes have a lower preference level, with the e-bike showing some attractiveness, whereas the step and scooter are in large not considered by respondents. When accounting for experience with such services however, we notice a substantial improvement in the preference for these modes, albeit still lower than walking, cycling or public transport.

Policymakers should therefore continue to put most effort and emphasis into strengthening the existing modes, providing a better level of service, higher availability and improving comfort. Yet for a significant number of people, shared electric modes are an interesting proposition and should thus not be fully excluded from the offering. Over time, as more users gain experience and through word-of-mouth and positive experiences of others, the use of electric shared modes is also likely to increase.

1. Introduction

Through its many externalities (emissions, noise, safety, space consumption,…) the mobility sector has a substantial impact on the quality of life of people around the world. Considering that mobility is the only sector where emissions have increased since 1990 (European Environment Agency, n.d.), the need to reduce externalities is even more pressing. In terms of everyday mobility of individuals, private internal combustion engine vehicles are the primary contributor of externalities. For distances beyond a few kilometres (what is comfortable to walk or cycle), public transport is one of the most sustainable alternatives, in terms of energy efficiency, safety and space consumption. Yet it often represents a fairly small share within the modal split (Prieto-Curiel & Ospina, 2024). Partly this is due to the quality of public transport itself (crowding, long(er) travel times, infrequent services, inconvenient ticketing,…). However, a substantial reason for the unattractiveness of public transport is the first/last mile problem: if people want to use public transport, they need to go to a stop/station to board a vehicle. In dense cities this can be a few minutes walk, but in less dense urban areas, suburbs or the countryside, the nearest stop can be hundreds of meters or even kilometres away. This makes using public transport very unattractive.

A recent study by Jonkeren & Huang (2024) analysed the potential of shifting car trips onto public transport in the Netherlands. Considering walking as an access/egress mode to public transport and no more than a 50% increase in the door-to-door travel time, only 0.9% of all car trips (2.5% of the total distance travelled) can be substituted. Allowing for travellers to access/egress public transport on the bike, this mode shift potential increases to 3.4% of trips or 7.8% of the travel distance. While still low, it represents more than a 3-fold increase from walking, showing the potential of the combination of bike and public transport. This shift is even more striking, when considering that these 3.4% of shifted car trips would result in a 90% increase in public transport trips. Jonkeren & Huang (2024) considered an upper bound of 5km for the access/egress distance, which is often used as the limit for a comfortable cycling commute. In one scenario, they did increase the maximum distance to 8km and the shifting potential increased further, to 7.8% of trips and 11% of the distance.

From the study of Jonkeren & Huang (2024), we can see that increasing the distance and speed of trips to/from public transport stops, public transport becomes vastly more attractive to replace car trips. But for longer distances, especially beyond 5km, even cycling becomes impractical for most. In recent years however, a variety of new forms of shared, often electric-powered mobility have entered the market, known collectively as micromobility (Abduljabbar et al., 2021). It includes modes such as bicycles, scooters, mopeds, hoverboards, roller-skates etc.

Several studies have been published in recent years, investigating the potential of these modes, their perception among travellers and what their role is within the mobility sector. Abduljabbar et al. (2021) carried out a review of recent findings and summarised that micromobility services tend to alleviate congestion, reduce emissions and address issues such as inequality and accessibility. They particularly point to improving the first/last mile as a major benefit. Considering induvial modes, scooters and mopeds are less beneficial as they sometimes displace walking and bike trips, high lifecycle costs due to high turnover and vandalism. On the other hand, de Bortoli (2021) reports that when considering everything together, there is little difference between a shared bicycle and an electric moped.

Considering the user and behavioural characteristics, most studies are in agreement as to the types of users using shared micromobility: they tend to be younger individuals, male, with an above average level of education, above average income and they tend to be fully employed (Badia & Jenelius, 2023; Christoforou et al., 2021; Mehzabin Tuli et al., 2021; Mouratidis, 2022; Nikiforiadis et al., 2021; Oeschger et al., 2023; Reck & Axhausen, 2021; Yan et al., 2023). Their primary motivation for using the services varies between contexts, with some studies finding price to be a deciding factor (Badia & Jenelius, 2023; Craver, 2024; Mehzabin Tuli et al., 2021; Zhu et al., 2022), while others reporting time savings as the main motivation (Christoforou et al., 2021; Esztergár-Kiss & Lopez Lizarraga, 2021). Shared micromobility tends to be used predominantly in dense urban areas (Badia & Jenelius, 2023; Romm et al., 2022) and mostly for leisure/social trips (Christoforou et al., 2021; de Wit, 2023; Esztergár-Kiss & Lopez Lizarraga, 2021).

One major topic of many publications is the role of (shared) micromobility in modal shift and particular its relation to public transport, whether it is a complement or competition. Most studies find mixed results, with micromobility acting both as a substitute as well as complement to public transport (de Wit, 2023; Luo et al., 2021; Nawaro, 2021; Ziedan, Darling, et al., 2021; Ziedan, Shah, et al., 2021). Micromobility tends to complement longer distance public transport, i.e. trains (de Wit, 2023; Liu & Miller, 2022; Romm et al., 2022), while substituting local public transport (buses, trams) and also walking and cycling (Badia & Jenelius, 2023; Christoforou et al., 2021; Nikiforiadis et al., 2021; Wang et al., 2022). Two literature review studies on micromobility (Abduljabbar et al., 2021; Zhu et al., 2022) both concluded that better integration between micromobility and public transport is needed and that much is still unknown in this domain.

To expand on the literature on micromobility and it's integration with public transport, this paper aims to get a better understanding of people's perception of micromobility, the valuation of time and different travel-related components and how they are willing to trade these off amongst each other. Specifically, we focus on the activity-end of the trip and how various shared micromobility solutions compete with existing alternatives. Research shows that the activity-ends of public transport trips tend to be shorter and less dominated by privately owned modes of transport (Stam, 2019).

In this paper, we will primarily look into the activity-end of a public transport trip, which is sometimes referred to in literature as an egress trip or the last mile. Home-end and activity-end refer to which side of the public transport trip the particular leg is happening on: between home and a public transport stop or between an activity location (work, school, cinema, sports centre,…) and a public transport stop. Access and egress (sometimes also called first and last mile) often refer to the same (access is often used for the home-end and egress for the activity end), but an access trip is always the trip or leg preceding the main public transport leg of the trip, while egress is always the succeeding leg. We typically view trips as originating at home and going to an activity, but if looking at the return trip, the access trip happens on the activity side and the egress on the home side. A graphic explanation of the terminology is included in Figure 1.

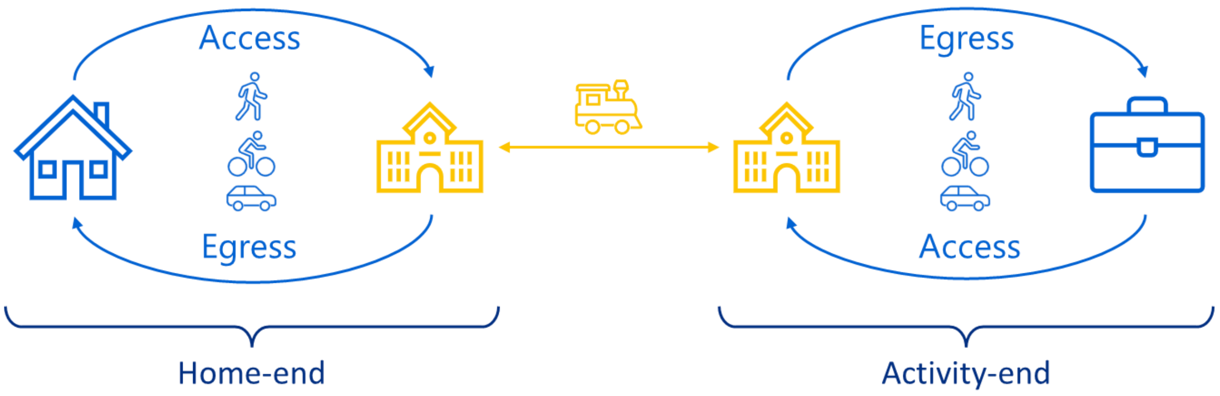

Figure 1. Terminology with access/egress trip and the home- and activity-end of trips

For trips on the activity end, we consider four different forms of shared micromobility, namely the bicycle, electric bicycle (e-bike), scooter and moped. The study is carried out in the Netherlands, where different terminology is used for scooter and mopeds: the standing scooter (shown on the left in Figure 2), which has emerged in the last decade, is known as a "step". A traditional sit-down version (shown in the right in Figure 2) on the other hand is primarily called a "moped". To avoid confusion with the word scooter, we will from here on out be using the words step and moped to refer to the two modes depicted in Figure 2.

Figure 2. A step (left) and moped (right)

The rest of the paper is structured as follows: the data collection and modelling approaches employed in the research are presented within the Methodology section in Section 2. The results are then outlined in Section 3, followed by a discussion on the implications of the results and an overall conclusion in Section 0.

2. Methodology

2.1 Survey design

To gain insights into the perception of valuation of different shared micromobility alternatives as a solution for the activity-end, we carry out a discrete choice analysis. To that end, we employ a stated preference (SP) discrete choice experiment. This is preferred to a revealed preference approach as we are able to much more carefully control the attributes and their variability. Additionally, SP experiments are better suited in instances investigating new alternatives with limited or no usage.

We devise an extensive SP experiment with a total of six alternatives. To make is easier for respondents and to obtain additional information, each choice task is split into two: respondents are first tasked to choose an egress mode among four different shared micromobility options, namely: (1) bicycle, (2) electric bicycle (e-bike), (3) e-step and (4) e-moped. Their chosen mode is then presented again next to (5) public transport and (6) walking. This way we can uncover the preference for different micromobility options in isolation and how they fit into the wider array of alternatives.

The alternatives are described by several attributes. Micromobility alternatives include (1) travel time, (2) travel cost, (3) walking time between the platform and vehicle, (4) type of rent (single or return) and (5) parking characteristics (free-floating, station-based or staffed station-based). The latter two are included as they form two key determinants of how shared micromobility services can be designed. According to Wilkesmann et al. (2023), micromobility sharing schemes can be one-way/single or return and free-floating or station-based. One-way refers to a vehicle being rented in one location and dropped off at another, whereas a return rent means that the vehicle must be returned at the same location as where it was taken. While the single rent approach gives travellers more flexibility and can make better use of vehicles, return rent is reliable for the return trip and requires little to no vehicle repositioning by the provider. Moving to parking type, the majority of shared micromobility services at the moment are free-floating, which means that a vehicle can be picked up and dropped off anywhere (within the service area). This often causes problems with vehicles being left on the street, on side-walks and being vandalised. Station-based parking (also referred to as docked) on the other hand has predefined locations where vehicles can be taken/left. To test if the presence of personnel increases the overall experience, we add that option to the station-based attribute level also. For public transport, (1) travel time, (2) travel cost and (3) walking time and (4) waiting time attributes are varied. The walking alternative only has a walking time attribute. An example choice task with the alternatives and attributes for the two choice tasks can be seen in Figure 3.

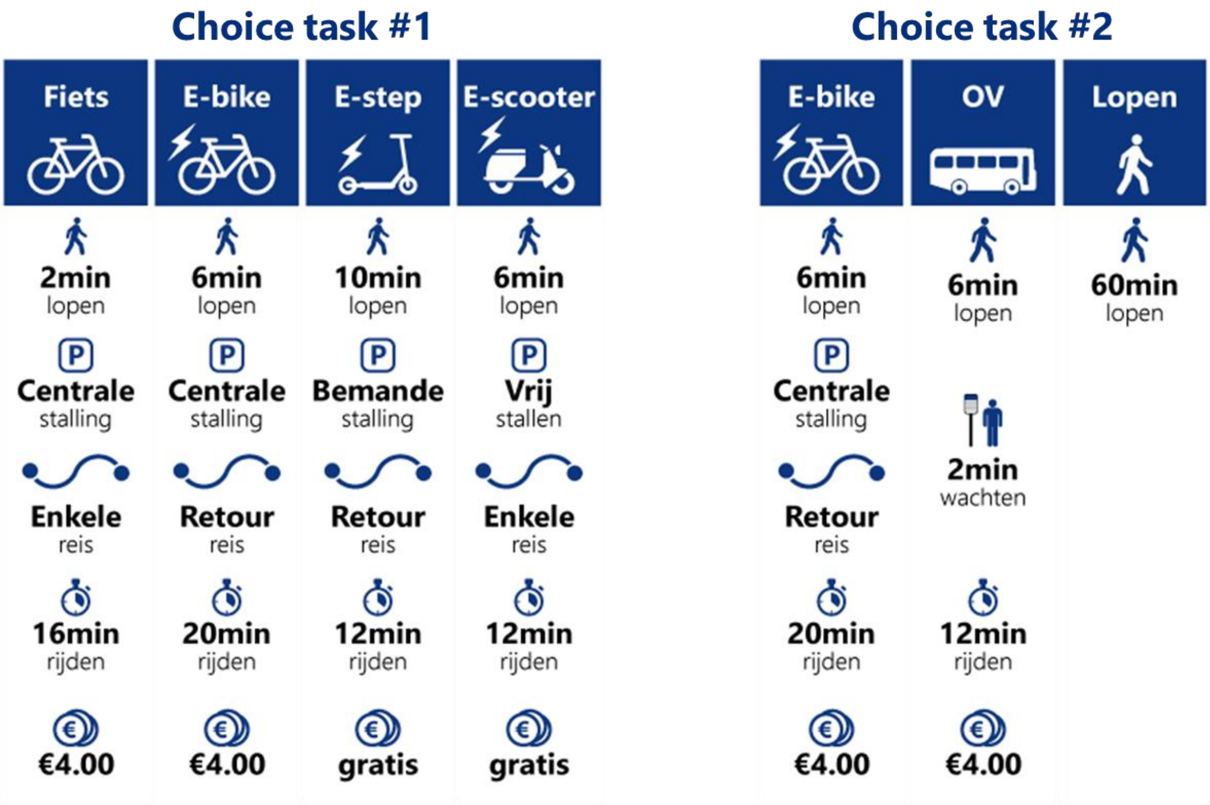

Figure 3. Example choice sets for the first (left) and second (right) choice task. In this example, the respondent chose E-bike in the first choice task, which is shown again in the second.

In addition to the choice tasks, the context of the trip is also varied: (1) the trip purpose, (2) the length of the train trip preceding the egress trip and (3) the distance from the station to the destination. Trip purpose is known to affect people's mode choice preferences and willingness to pay (Geržinič et al., 2022), so the trip is either to work/education or for a social activity with friends/family. The train trip is varied because previous research found that for longer trips, travellers are willing to make longer access/egress trips (Krygsman et al., 2004). In the survey, train trips vary between 15min, 45min and 75min, capturing the majority of train trip lengths while also keeping equidistance between levels (see Figure 4). Finally, egress trip distance is varied to assess the preferences for different modes across varying trip distances and in particular if electric modes may be more attractive for longer distances. We test distances of 1km, 4km and 7km. These values are not conveyed explicitly, but rather we use them to impute possible travel time and cost attribute levels. As we use three levels for each attribute, that provides with additional variation in each distance class and thus good overlap across the classes. The tested values also align well with the tested values of Jonkeren & Huang (2024); although they tested 8km as the furthest range, the additional variation we apply onto the 7km distance class is able to capture distances of up to 8km.

We use Ngene (ChoiceMetrics, 2021) to obtain the survey design. We use simple priors, indicating only the expected sign (negative) for travel time, walking time, waiting time and travel cost, whereas other priors are set to zero as we do not have sufficient information on the preference. Together with the context, we obtain a total of 54 choice sets, which we block over six blocks into nine choice tasks per respondent. Within those, a group of three choice tasks has the same context (trip purpose, train trip length, egress trip distance), meaning that each respondents is shown three different context combinations. Respondents are randomly allocated to one of the six blocks.

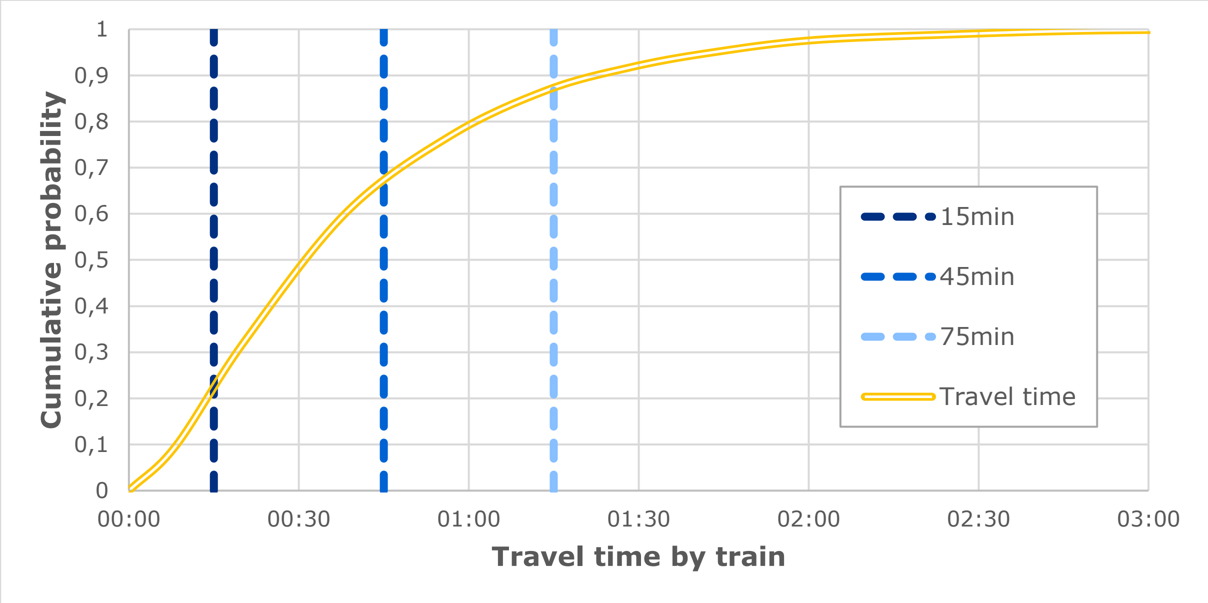

Figure 4. Cumulative distribution of train travel times and the context levels tested

2.2 Model estimation

The obtained data is modelled by means of a discrete choice model is specified using the Pandas Biogeme package in Python (Bierlaire, 2023). The model is estimated based on the assumption that respondents try to maximise their expected utility when making trade-offs (McFadden, 1974). We estimate a series of multinomial logit (MNL) models, testing different specifications of parameters to capture non-linear perception of attributes, interaction effects and the impact of socio-demographics and current travel behaviour on mode choice.

The model is then extended utilising a mixed logit model (MXL) formulation, which provides three additional benefits which can help in improving model fit and improving the understanding of preferences of individuals. Firstly, MXL models account for the panel effect, meaning they treat all the responses from one respondent as the same person (Train, 2009). Traditional MNL models consider each choice made independent of all other choices, including the unobserved error terms. But the unobserved error terms of the same respondent should stay the same throughout the choices they make.

Secondly, MXL models allow for analysing the heterogeneity in behaviour among respondents (Train, 2009). Parameters can be randomised, meaning that they are distributed and an individual's perception of an attribute can fall anywhere on the distribution. This allows us to analyse the range of trade-off behaviours that can be expected within a population.

Finally, MXL models enable us to account for potential nesting structures within the data. MNL models assume that all alternatives are independent of each other, while this may not be the case (Train, 2009). In this study, there is reason to believe that all micromobility modes may have certain unobserved similarities, which are not shared with walking and public transport. Further, the bicycle and e-bike may also share similarities between them that is not shared with other modes. These groups are called nests and by specifying a nesting parameter, we can ascertain if individuals perceive them to be more similar. In other words, we can determine the level of correlation between alternatives.

To compare the many estimated models, several model outputs can be compared to determine the best performing model. The final loglikelihood and rho-square are direct indicators of how well the model fits the observed data, with the latter indicating the level of fit between 0 (random) and 1 (perfect fit). These indicators do not take the number of parameters into account, meaning they do not provide information on the efficiency (parsimony) of a model. To that end, we employ two indicators, namely the adjusted rho-square and the Bayesian Information Criterion (BIC) (Train, 2009). Both take the into account the model fit and the number of parameters used in the model estimation, where the BIC is more strict in penalising additional parameters in the model formulation.

2.3 Data collection

The survey is distributed among the members of the Dutch Railways' panel (NS, 2020) between 29.07. and 31.08.2024. Preliminary results include all the responses collected up until 15.08.2024 and presented further in this paper. The preliminary results include a total of 1,703 responses. 66 did not consent to participating in the survey and 468 did not complete all the choice tasks. On the 1,169 complete responses, we apply several filtering techniques. Firstly, we check for straightlining behaviour on the attitudinal statements; respondents who replied with the same answer to multiple/all questions. We apply this on the attitudinal statements, removing 5 responses that always filled in the same opinion. Next, we remove the speeders by analysing the response times. According to Qualtrics (2024), responses shorter than the median minus two standard deviations can be considered as too fast. Based on this criterion, a further 10 responses are removed. After the filtering, we are left with 1,154 valid responses. The distribution of response times and different groups of responses removed can be seen in Figure 5.

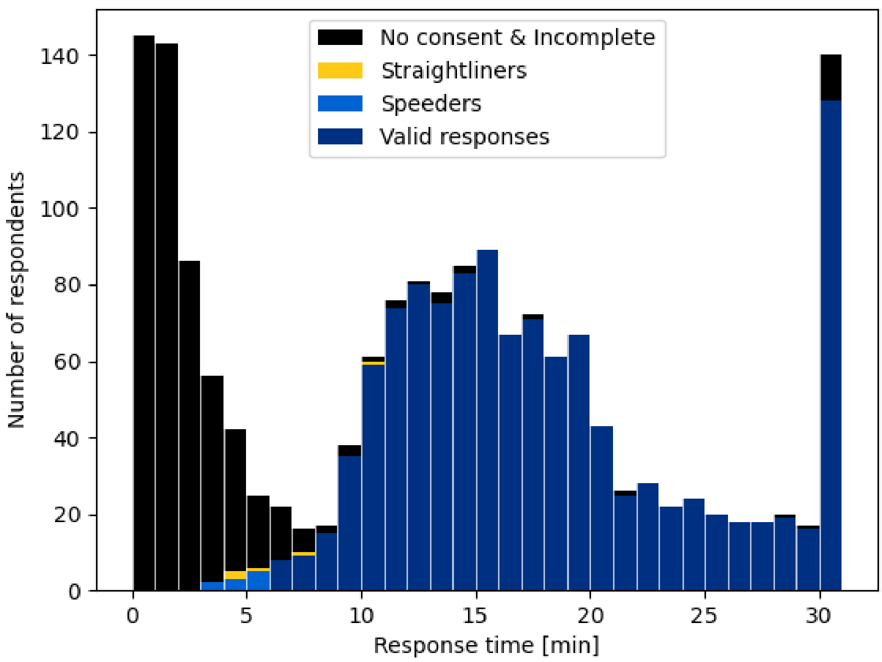

Figure 5. Response time distribution

3. Results

On the data collected up until 15.08.2024, we estimate a series of choice models. We start by estimating an MNL model to use as a baseline for comparison with more advanced models. We then estimate an MNL model with several interaction effects, to test the effect of different contexts and potential non-linear perceptions of parameters. Finally, we estimate an MXL model to account for the panel effect, test the heterogeneity in perception of a variety of attributes and to analyse potential nesting effects among parameters. The model fits of all three models are presented in Table 1. The full model outcomes, including parameter estimates, are only presented for the MXL model, in Table 2.

Table 1. Overview of model outcomes

	Baseline MNL	MNL with interactions	MXL model
Parameters	12	58	27
Final LL	-12,226	-11,664	-9,593
Rho-square	0.3430	0.3732	0.4845
Adjusted Rho-square	0.3424	0.3701	0.4831
BIC	24,564	23,865	19,435

Through the three models, all three time-related parameters stay fairly consistent, with the willingness-to-pay (WtP) for improvements in in-vehicle time around 13€/h, 16-17€/h for improvements in waiting time and 19-21€/h for walking time. These are well in line with current Dutch WtP levels (Kouwenhoven et al., 2023). Contradictory to most findings (Wardman, 2004), walking time is valued more negatively than waiting time. Nevertheless, both values are in the range of 1.5-2.5x more negative than the in-vehicle time, which is again within the expected range. We also test for marginally increasing perception of the three time parameters by estimating quadratic components. The ones for in-vehicle and waiting time are insignificant. The quadratic component for walking is significant, however the impact is minimal.

For the cost parameter, we do not include a quadratic component, but we do test for the different perception of a service being offered for free. This turns out highly significant and also showing a strong impact. If a service is offered for free, it is seems to be perceived as if the respondents are paid €2 to use it.

Table 2. Parameter estimates of the MXL model

	Parameter estimate	Robust t-stat [param]	σ	Robust t-stat [σ]
Constants				
Bicycle	-2.5242	-16.14**	1.6221	11.09**
E-Bike	-4.1196	-20.73**	-0.7777	-2.57*
Step	-6.3132	-23.18**	1.1756	3.87**
Moped	-6.9301	-26.95**	1.3927	8.21**
Public transport	-2.2727	-14.72**	2.5527	17.20**
Taste parameters				
Cost	-0.4372	-29.64**		

In-vehicle time	-0.0966	-16.92**		
Waiting time	-0.1163	-10.00**		
Walking time	-0.1375	-23.73**		
Free-floating parking			-0.4380	-3.63**
Central parking	-0.1913	-2.81**	0.2865	1.46
Manned parking	-0.1194	-2.17*	0.0179	0.55
Single rent			-0.5346	-3.81**
Return rent	0.3474	6.00**	-0.5079	-3.38**
Nesting parameters				
Bicycle nest	0.3634	2.06*		
Electric modes nest	2.3263	14.52**		
Non-shared modes nest	1.2719	3.52**		
Step-Moped nest	1.2052	5.51**		
Shared modes nest	1.6090	6.91**		

*** p≤0.01, * p≤0.05*

Investigating the preferences for the different modes, we can observe the same pattern in all three models, whereas the magnitude of the difference is different. For the model with interactions, this can be explained by the latter, as many interactions are linked to modal preferences. For the MXL model, accounting for heterogeneity and including the nesting effects also affects the value of ASCs. In all three models, (1) walking (the base alternative) is the preferred egress mode (ceteris paribus), followed by (2) public transport and (3) the shared bicycle that perform very similarly in all three models. They are followed by the (4) shared e-bike wile the (5) step and (6) moped taking up the last spots at almost equal (dis)preference and not always in this order. This variation of preferences for different modes within the MXL model is highlighted in Figure 6.

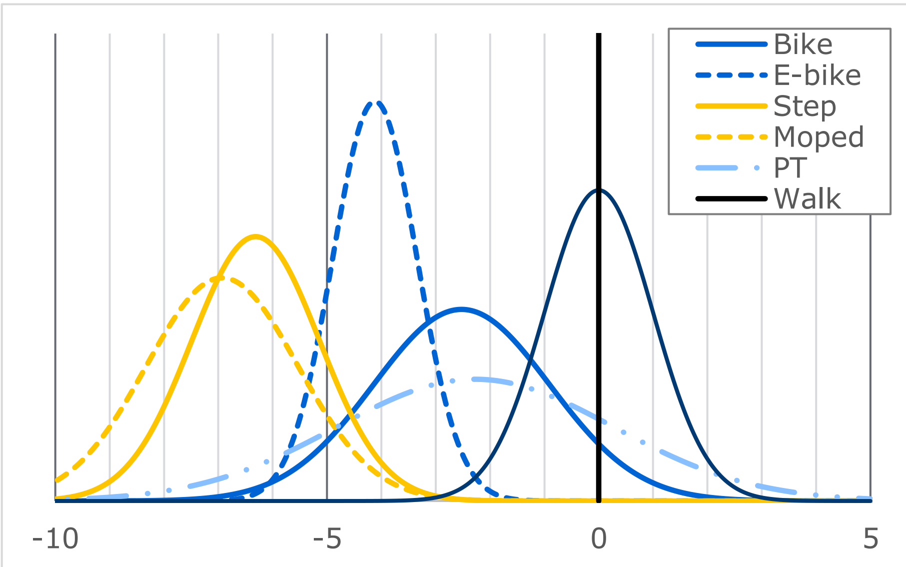

Figure 6. Preference variation for different modes

Considering what affects modal preferences, several interactions with trip purpose and current travel behaviour have been tested. Firstly, we observe that trip purpose (work vs. leisure) has a limited impact on the overall preference for a mode, with only the preference for moped decreasing in case of a leisure trip, whereas all other interactions are insignificant.

Next, the length of the train trip also does not seem to have an effect on the mode preferences, with a single parameter showing a weak albeit significant effect, namely that for longer train trips (75min), travellers will have a slight additional preference for taking public transport as an egress mode.

Turning to the influence of current travel behaviour, we highlight the significant interaction parameters, which are a few and with predominantly minor impacts. Respondents who currently use the bicycle on a weekly basis (at least 1x per week) do not differ substantially from the baseline. A small additional utility is observed for the ASC for e-bike and a small disutility for PT. Interestingly, frequent train users (at least 1x per week) are more likely to opt for a shared moped or step for an egress trip, compared to less frequent train users. For those who (almost) never use a car (infrequently on a yearly basis) are more likely to choose public transport, and less likely to opt for a shared scooter.

Lastly, we asses the influence experience with different sharing services has on mode preference. Here, the impacts are stronger and more parameters turn out significant. To showcase the differing preferences given past experience, we split the sample into four groups, based on the experience of using OV fiets and other shared services. As we can see in Table 3, about a third of respondents have no experience with any shared service. The largest share have used OV fiets, but not other shared modes. Another quarter have used both, while only a small fraction used other shared modes, but not OV fiets. Those who have previously used OV fiets (the bike sharing service of the Dutch railways) are much more likely to also opt for the bike in the SP experiment. A slight preference can also be observed for the E-bike, and a dispreference for PT. Having used any other shared service before (moped, e-bike, car) has a positive and significant impact on all shared modes, with the impact being strongest for moped and step.

Table 3. Contingency table for experience with different shared transport services

Have you ever used:		Other shared modes		
		Yes	No	Σ
OV fiets	Yes	279 (24%)	497 (43%)	**776**
	No	41 (4%)	337 (29%)	**378**
	Σ	**320**	**834**	**1,154**

Next, we look at the types of parking (Figure 7) and rental (Figure 8) approaches. In both cases, we see significant overlap between the different implementation schemes. When considering parking, it seems that a free-floating approach is preferred, although the overlap with the distribution of central parking is significant. And in the results of the MNL model with interactions also shows that when adding interactions, the difference between means becomes insignificant, meaning that in the form without interactions, they may be capturing a different effect.

In terms of the type of rental, a return may be slightly preferred, to a value of ~€0.80, which is not substantial. Again, this may come down to personal preferences, where some respondents rather opt for the flexibility of the single rent, whereas other s prefer the reliability of the return approach.

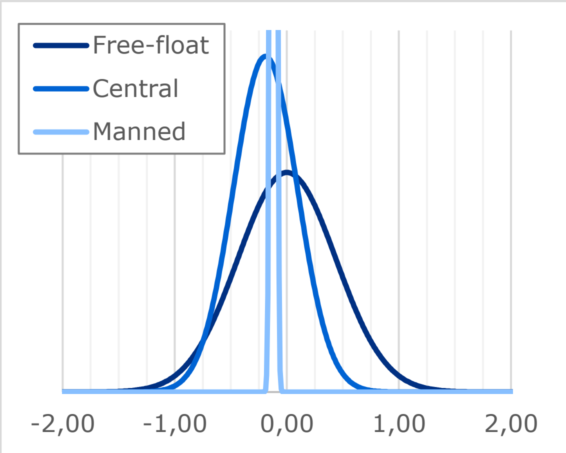

Figure 7. Distribution of preferences for parking policies

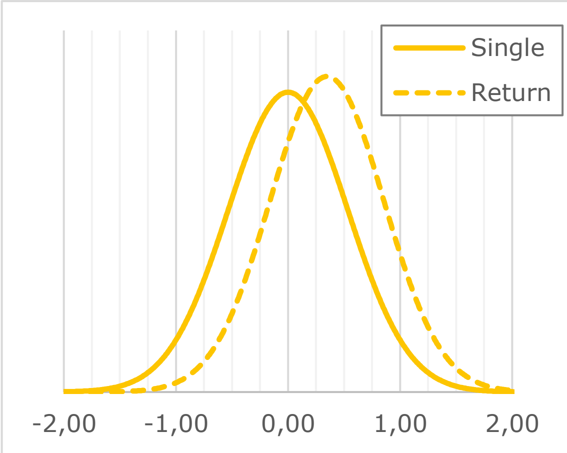

Figure 8. Distribution of preferences for rental schemes

Finally, we analyse the nesting effects that can be observed among the alternatives. Doing this by means of an MXL model allows us to test for cross-nesting as well, where an alternative can belong to multiple nests at the same time. In particular, we test five different nest specifications, namely:

1. **Non-sharing nest**: Public transport, Walk
2. **Shared nest**: Shared bicycle, Shared E-bike, Shared Step, Shard Moped
3. **Bicycle nest**: Shared bicycle, Shared E-bike
4. **Electric nest**: Shared E-bike, Shared Step, Shard Moped
5. **Step-Moped nest**: Shared Step, Shard Moped

Although all five nesting parameters are significant, most show a limited rate of correlation and therefore limited nesting effects among the alternatives. The weakest effect is seen for the bicycle nest, with a correlation of only 0.18. The non-shared, shared and step-moped nests are all in the correlation interval of 0.4-0.5, which is still weak albeit somewhat influential. The Electric nests performs the strongest, with a correlation of 0.59. the electric nest also captures all the "new" modes in a way, as those are the shared modes that the majority of respondents are likely not familiar with.

4. Conclusion and implications

This paper presents the first insights into a larger study on passengers' perception and preferences towards shared micromobility services as an access/egress mode to train stations. From the data already collected, we observe that overall, people prefer to reach their destination from the station on foot, only opting for other modes for longer egress journeys. We see that this switching to other modes starts at a when walking times exceed 15min, with those who have past experience with shared services opting for a bike or PT at 15min egress walking time, whereas those without any past experience will switch to PT at 15min, but to bike or e-bike only at 25min of walking time. This highlights many previous findings, that familiarity with a service is one of the strongest predictors of future use. From our results, we see that this effect is stronger than trip purpose, train trip length or current travel behaviour.

With respect to design characteristics of such services, we find no strong preference for the type of parking (free-floating, centralised or with personnel) and for a single vs. return trip-type rent. In both cases, the differences were minor or even insignificant. When accounting for heterogeneity among participants, we conclude that the overlap between distributions is substantial and essentially each person will have a different preference order. In other words, there is not a single favourite within the population, but rather is user-specific.

In terms of time parameters, we report a WtP in line with Dutch standards of ~10-15€/h and a higher WtP for walking and waiting times, also falling within the scope of expected values.

Despite the importance of past experience, our results still show that cycling and public transport are the dominant and most preferred access/egress modes to train stations for distances beyond a comfortable walking distance/time of ~15min (~1km). Policymakers and operators should therefore not overestimate the potential of new modes and rather focus on improving the quality and availability of the existing options which have proven themselves popular among the travelling public.

An interesting finding to potentially investigate further is also the integration of access/egress travel directly in the ticket price of the train trip. By estimating the perception of a free egress mode (no additional cost), we notice a non-linear effect in attractiveness for any of the modes. Deeper integration, such as was shown through the many MaaS trials (of ticketing, information,…) is also proven to be more attractive option for individuals when travelling.

This survey assumes that taking the train is a given and that an alternative completely circumventing the train trip (by car for example) is not considered in this case. Such an analysis may show different results and perhaps new modes may entice current car users to switch to train, although existing literature on this topic is not very promising.

In the future, we will extend the survey to a second panel, capturing less frequent users of trains in order to obtain more information from individuals who are currently less likely to use trains and therefore also micromobility as an egress mode. We aim to extend the models by adding the attitudinal statements that have been included in the survey. We will estimate further MXL models and also extend the MNL formulation to a latent class (LC) model. Like the MXL, the LC model also accounts for heterogeneity, but rather than allocating individuals along a distribution, a discrete number of classes are imposed onto the sample, each with its own unique MNL parameters, creating distinct user groups with their own WtP values indicating their own unique trade-off behaviour. Additionally, we are able to obtain the socio-demographic and travel-related characteristics of each of the groups, further enhancing the information of each group.

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